# Remote Sensing Data Quality in the Era of AI

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**Abstract**

The era of Artificial Intelligence ‘AI’ with all the benefits brought along, has raised new and additional challenges to the ongoing efforts of assessing, defining, formulating, and implementing the quality aspects of geospatial remote sensing data. Developed practices using artificial intelligence leveraged techniques such as image interpretation, classification, thematic mapping, and even image quality enhancement, necessitating by that the reassessment and redevelopment of some of the related emerging quality aspects. Moreover, technology also made the generation of false images and false data possible, this matter constrained and increased precaution and doubtfulness, altogether making some practices based on that data almost halt to further notice.

This paper presents the collaborative research work to assess and clarify the quality aspects that arose with the advent and implementation of AI and associated technologies; the concerns and issues that can accompany the generation of false satellite and aerial images including the generated geospatial data out of which, how the new emerged quality aspects fit into the currently existing methods through the lifecycle of remote sensing data production and usage, and consequently how the quality dimensions are affected and should be further developed and improved to tackle the changes and innovations. Also, lame a bit on investigating how to accommodate the new challenges in standards, and practical procedures and raise the awareness to users, the level of dependency on improved and enhanced satellite images when it comes to data collection interpretation and classification, and finally define the research gaps, future expected challenges and thus enclose suggestions and recommendations in that respect.

## 1. Introduction

It’s evidently approved through current practices that the era of Artificial intelligence has brought many positive advantages and profited the world in many aspects like advancing technologies, automating processes, and generating new data and information that couldn’t have been possible otherwise. However, it also started to appear that favourableness in this theme is not always the case, as some AI's undesirable effects began creepily sweeping and climbing many technology disciplines, procedures, analysis, and data productions including those related to geospatial science and technology. Thus, unless proper measures are taken and quality inovated standards and procedures are upgraded to cope with issues, unpleasant consequences can occur.

Actually, the remotely sensed products are not exempted either, as the new technology benefited many operations including image interpretation and classification also image quality enhancement, but again simultaneously became susceptible to being victimized too. The necessary need for revised quality regulations and practices strongly imposes itself, especially with the existence of AI generativity which indisputably can lead to improper decision-making, which then tends to cause risk probability for natural and artificial calamities and destruction scenarios, unless proper actions are taken against which [Aleissaee et al., 2023; Janga et al., 2023].

The conventional quality aspects of data produced via the technology of remote sensing are looked into for addressing the new challenges that evolved with the advent of the integration and implementation of AI machine learning, deep learning algorithms, and generative AI. This sistering and merging of technologies had escalated the challenges of assuring the reliability of the remote sensing data and the geospatial data in general, and thus the information and knowledge produced out of that.

The flow representing this work shall start by addressing the era of AI and how it affects remote sensing in general and discuss some possible future aspects of this not-totally new but rapidly emerging relationship. This will take you on a trip through artificial intelligence, types and usage, discussions, and future trends.
This is followed by a chapter dedicated to AI interactions with the lifecycle of the remote sensing process and how that affects individual data dimensions.
Further, a chapter is dedicated to a bit deeply indulging into how generative AI could be harmful unless carefully handled with knowledgeable notions and precaution.
The final chapter before the conclusion and closer will then discuss the data quality aspects of the practical implementation of AI and deep learning in data interpretation and classification, which particularly discusses certain aspects related to the workflow of implementing remote sensing for detecting urban changes and mapping thematic land use \ Land cover maps in a


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topographic scale if scale makes sense in the era of AI applications as many users consider that as history.
This will open the stage for practically analyzing how the implementation of AI technology in image interpretation and classification affects the reliability and quality aspects of the resulting data, and what types of metrics portray the quality.

## 2. The application of Artificial Intelligence in Remote Sensing and the effect on data quality and the use of deep learning

Artificial Intelligence (AI), particularly deep learning, has significantly impacted remote sensing across various aspects, including data acquisition, processing, analysis, and interpretation. The integration of AI, particularly deep learning, in remote sensing enhances data quality by automating data processing, improving feature extraction and classification, facilitating change detection, enabling data fusion, and automating quality control processes. These advancements contribute to more accurate, comprehensive, and timely analysis and interpretation of remote sensing data for various applications. By leveraging AI techniques such as deep learning, remote sensing practitioners can improve data quality, extract valuable insights, and automate various aspects of data analysis and interpretation, thereby advancing the capabilities of remote sensing technology for diverse applications.

### 2.1 Applied AI Techniques in Remote Sensing

The effects on data quality and its application, starting from data acquisition and pre-processing where Automated Correction using AI algorithms can automatically correct various distortions in remote sensing data, such as atmospheric interference, sensor noise, and geometric inaccuracies. For instance, techniques like neural networks can learn to model and correct atmospheric effects in satellite imagery, improving data quality. Also, Resolution Enhancement where Deep learning-based super-resolution techniques enhance the spatial resolution of remotely sensed imagery, allowing for the generation of higher-quality images from lower-resolution inputs. Generative adversarial networks (GANs) and convolutional neural networks (CNNs) are commonly used for this purpose. AI algorithms help improve data quality by automating the process of image correction, such as atmospheric correction, radiometric calibration, and geometric correction.

Deep learning models can enhance image resolution through techniques like super-resolution, enhancing the quality of remotely sensed data. In feature extraction and classification, Semantic Representation using Deep learning models, especially CNNs, are adept at learning hierarchical representations of features in remote sensing data. By processing raw imagery through multiple layers, CNNs can extract intricate spatial and spectral features, enabling more accurate classification of land cover types, terrain features, and objects of interest. Transfer learning techniques leverage pre-trained deep learning models on large datasets to adapt them to remote sensing tasks with limited labeled data. This approach is particularly useful in scenarios where acquiring labeled training data is expensive or time-consuming.

Deep learning techniques like Convolutional Neural Networks (CNNs) excel in extracting features from remote sensing imagery, enabling more accurate classification of land cover types, infrastructure, and other features.AI algorithms facilitate automated object detection and recognition in imagery, contributing to improved data analysis and decision-making. AI algorithms aid in change detection by comparing images from different periods and identifying areas of change or land cover transformation. Deep learning models can detect subtle changes in large-scale landscapes, improving the monitoring of environmental changes, urbanization, and natural disasters. Temporal Analysis is the application of Deep learning models to analyze temporal sequences of satellite imagery to detect changes over time. Recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks are commonly used for time-series analysis of remote sensing data, enabling the identification of land cover changes, deforestation, urban expansion, and other dynamic phenomena. Unsupervised learning algorithms, such as autoencoders and clustering techniques, are employed for change detection without requiring labeled training data. These methods identify significant deviations between image patches or feature distributions in different periods, indicating areas of change (L. Zhang & L Zhang, 2022).

AI techniques facilitate data fusion through the integration of data from various sources, including optical, radar, and LiDAR imagery, to create comprehensive and accurate datasets. Deep learning-based fusion methods enhance the synergistic utilization of different data modalities, leading to improved understanding and analysis of remote sensing data. Multi-Modal Fusion. Fusion methods based on deep learning, such as multi-sensor fusion networks, integrate diverse data modalities for applications like land cover mapping, disaster monitoring, and urban planning. Attention Mechanisms: Attention mechanisms in deep learning architectures allow models to selectively focus on relevant information from different data sources during fusion, enhancing the accuracy and robustness of fused datasets (Adel Mellit & Soteris Kalogirou, 2021).

Deep learning models, particularly semantic segmentation networks like U-Net and object detection frameworks like YOLO (You Only Look Once), segment remote sensing imagery into pixel-wise categories, enabling detailed land cover mapping and feature extraction to enable precise delineation of objects and regions of interest in remote sensing imagery. These models leverage fully convolutional architectures and spatial-contextual information to produce high-resolution segmentation masks and contribute to improved data interpretation, land cover mapping, and infrastructure monitoring. Object Detection: Object detection frameworks like YOLO (You Only Look Once) and Faster R-CNN (Region-based Convolutional Neural Network) enable the detection and localization of objects within remote sensing imagery, such as buildings, roads, vehicles, and natural features. These models employ region proposal methods and bounding box regression to identify objects of interest with high accuracy and efficiency (Adel Mellit & Soteris Kalogirou, 2021).
Techniques such as gradient-based attribution methods and saliency maps highlight important pixels or regions in imagery, aiding in the interpretation of classification results and decision-making.

Finally, AI-based quality control methods help identify and correct errors in remote sensing data, ensuring data accuracy and reliability. Deep learning models can detect anomalies, such as sensor malfunctions, data artifacts, and unexpected environmental changes, and inconsistencies in imagery, enhancing data quality assurance processes. These techniques leverage unsupervised learning and anomaly-scoring mechanisms to flag data instances requiring further investigation or correction. AI algorithms aid in error correction and artifact removal in remote sensing imagery through techniques like inpainting, where missing or corrupted regions are filled in based on surrounding context learned by deep neural networks. This process helps enhance the visual quality and integrity of remote-sensing datasets. (Y. Xu et al., 2023).

### 2.2 Future Aspects

Looking ahead, the application of Artificial Intelligence (AI) in remote sensing is poised for significant advancements, accompanied by both opportunities and challenges. Addressing these challenges will require interdisciplinary collaboration among researchers, practitioners, policymakers, and stakeholders to develop robust, transparent, and ethically sound approaches to the application of AI in remote sensing. By overcoming these challenges, AI has the potential to revolutionize remote sensing, enabling more accurate, timely, and actionable insights into our changing planet's dynamics and supporting sustainable environmental management and decision-making. Future applications will increasingly leverage the integration of multi-modal remote sensing data, including optical, radar, LiDAR, and hyperspectral imagery.

AI techniques will play a crucial role in fusing and analyzing diverse data modalities to extract comprehensive and accurate information about the Earth's surface and atmosphere. Enhanced Spatial and Temporal Resolution through Deep learning algorithms will continue to improve the spatial and temporal resolution of remote sensing data, enabling finer-grained analysis and monitoring of dynamic environmental processes, urban development, and natural disasters. Real-time monitoring and Response using AI-driven remote sensing systems will facilitate real-time monitoring and rapid response to environmental changes, such as deforestation, wildfires, floods, and pollution. Autonomous drones equipped with AI-powered sensors will enable agile and adaptive environmental monitoring and disaster management. Also, the Semantic Understanding and contextual reasoning of AI models will exhibit improved reasoning capabilities, enabling a more nuanced interpretation of remote sensing data. These models will understand complex spatial relationships, temporal dynamics, and environmental contexts, leading to more accurate and insightful analysis (Adel Mellit & Soteris Kalogirou, 2021).

Interpretability methods will enable users to understand how AI models arrive at their predictions and decisions, fostering confidence in AI-driven analyses. Automated Data Quality Assurance driven by AI techniques will become increasingly sophisticated, automating the detection and correction of errors, artifacts, and anomalies in remote sensing data. Future efforts will focus on addressing data bias and improving the generalization capabilities of AI models in remote sensing. Techniques such as domain adaptation, transfer learning, and synthetic data generation will help mitigate biases and enhance the robustness of AI-driven analyses across diverse geographic regions and environmental conditions. Finally, as AI becomes more pervasive in remote sensing applications, there will be a growing need to address ethical and societal implications, including privacy concerns, data ownership, and equitable access to technology and information. Responsible AI frameworks and governance mechanisms will be essential to ensure the ethical and equitable deployment of AI in remote sensing (Jose Garcia-del-Real & Manuel Alcaráz, 2024).

### 2.3 Further Reliability & Quality Challenges:

Despite advances in automated data processing, ensuring the quality and consistency of remote sensing data remains a challenge. Labeling large-scale datasets for training AI models can be labor-intensive and costly, especially for specialized tasks and rare phenomena. The black-box nature of some AI models poses challenges for interpretability and trustworthiness, particularly in critical applications such as environmental monitoring and disaster response. Balancing model complexity with interpretability will be crucial for fostering trust in AI-driven analyses. The increasing volume of remote sensing data raises concerns about data privacy and security, especially when sensitive or personal information is inadvertently captured. Developing robust data anonymization and encryption techniques will be essential to protect privacy while maximizing the utility of remote sensing data.

AI algorithms trained on biased or unrepresentative datasets can perpetuate and exacerbate existing biases in remote sensing analyses. Addressing algorithmic bias and ensuring fairness and equity in AI-driven decision-making will require careful attention to data collection, model training, and validation processes. Deploying AI models for large-scale remote sensing applications poses challenges in terms of scalability and resource constraints, particularly in resource-limited environments or developing regions. Optimizing AI algorithms for efficiency and scalability will be essential to enable widespread adoption and deployment. Regulatory frameworks and ethical guidelines for AI in remote sensing are still evolving, leading to uncertainties and ambiguities in terms of legal and ethical responsibilities. Clarifying regulatory requirements and ethical norms surrounding AI-driven remote sensing will be essential to ensure responsible and accountable use of technology.

## 3. Effects of AI technology on RS data quality dimensions and data life cycle

A general approach to clustered data and information quality dimensions has been developed by Batini and Scannapieco (Batini and Scannapieco, 2016). It has been adapted to remote sensing data by [Barsi et al., 2019]; in their paper, the authors gave detailed definitions for each component of the individual data dimension clusters and presented the related dimension metrics for it. In this context, the remote sensing data life cycle phases were also defined. Based on the previous findings the current paper reviews the effect of AI on those mentioned measures.

### 3.1 Data quality dimensions

The Resolution cluster (spatial, radiometric, spectral, temporal resolutions, and point density) is an important quality measure of the data acquisition process, even though it accompanies the entire life cycle. Currently, AI is having a major impact on the spatial resolution of imageries in addition to the point density dimensionality of 3D point clouds (e.g. from different laser scanning technologies). As processing tools were developed to target superresolution at these characteristics and strive to improve them [Li et al., 2019; Li et al., 2022; Romero et al., 2019; You et al., 2023; Zhang et al., 2022].

Accuracy cluster dimensions such as geometric, spatial, radiometric, spectral, temporal precisions, spatial, radiometric, and temporal accuracies are similarly related to the acquisition and, therefore the effect is again less significant. On the other hand, the remaining two dimensions specifically – classification and semantic accuracy – are of extreme importance when it comes to their relation to AI and associated effects, and that's because they are derived using Remote Sensing data processing and are crucial in expressing the quality of the output. It is common knowledge that the AI tools used for thematic mapping

of remotely sensed images became widely applied, which enhanced quality characteristics compared to traditional processing methods. Relevant papers on this topic are [Anilkumar et al., 2021; Chen et al., 2021; Jiang et al., 2023; Sen and Keles, 2020; Song et al., 2019; Thapa et al., 2023].
In the case of the Completeness dimension cluster (data, spatial, stereo, temporal completeness), thematic completeness can be impacted, since it is the only dimension that is interpreted in the processing chain; others are characterizing data acquisition.
The Redundancy cluster (spatial and temporal redundancy) provides information on the nature of the processing preconditions; in this topic, AI can be studied more in terms of how its specific features (especially the accuracy dimension) relate to these dimensions.

The Readability cluster with spatial readability and radiometric readability expresses how objects can be identified/separated in a spatial and radiometric context for data interpretation. Unfortunately, in the majority of cases AI for remote sensing image analysis delivers quality measures solely in the form of confusion matrices (see the Accuracy cluster) and some additional measures derived from them. Thus no further dedicated readability measures are computed. Other approaches, like object detection, provide basic statistics about certain object types occurring in the images.
The Accessibility cluster (temporal and data accessibility) only qualifies access to remotely sensed data as sources not relevant to this study.

The Consistency dimension cluster includes the geometric, thematic, topological, and temporal dimensions. By its nature, this cluster strongly characterizes the quality of image interpretation/understanding. In remote sensing, spatial consistency encapsulates geometric, thematic, and topologic consistencies within the cluster. This measure assesses the quality of image interpretation, specifically the comprehensive recognition and evaluation of distinct objects or classes. Thematic consistency pertains to the integrity of recognition, reflecting the uniformity with which thematic classes are identified across the area of interest. Topologic consistency measures the connectivity and validity of object topology. In the context of urban mapping, particularly with respect to built-up environments, the inclusion of house parcels is characterized by the consistency dimension. As it follows from the above, the various AI-based image analysis techniques, especially object recognition solutions, can of course be considered by these dimensional elements.

### 3.2 Data life cycle

As discussed by the authors in the [Barsi et al., 2019], there are four major data life cycle phases in remote sensing. Having reviewed these, we now can describe the role and impact of AI on the phases.
In the Data acquisition phase, data source selection, data reading/data capture and sensor calibration are included as part of the life cycle. The first two specifically discuss the acquisition of data. Since the primary purpose of remote sensing is to collect data about the real world, artificial intelligence does not play a role here. AI-generated fake space images may appear among the available data, which will be discussed later.
Traditional sensor calibration typically relies on hand-crafted features and complicated mathematical models. Learning-based methods provide a fully automatic camera calibration solution without manual intervention or calibration targets, which sets them apart from traditional methods. An excellent review paper is provided by [Liao et al., 2023] on the general objective of camera calibration which can also be easily adapted to remote sensing devices.

The Data storage phase includes data format management, data compression, data replication, and data distribution. AI-based image compression methods such as the transformer neural network solutions are efficient technologies for managing large image collections. The technology offers several pre-trained deep neural network models with various compression efficiency and stored image quality. Learning-based image compression can be characterized as utilizing advanced, adaptive algorithms that significantly enhance the efficiency and quality of compression compared to traditional techniques. These advanced methods dynamically optimize compression in real-time, resulting in higher-quality images at lower data sizes [Balle et al., 2018; Bégaint et al., 2020; Cheng et al., 2020; Horváth and Barsi, 2022; Toderici et al., 2016].
The most common and most diverse data life cycle group is the Data preprocessing, processing, and analysis phase. This includes the following groups of procedures:

- restructuring
- data selection
- sampling, resampling
- filtering
- feature extraction
- segmentation
- clustering
- classification
- sensor/data fusion
- optimisation
- abstraction.

As this group is widely applied and diverse, we will focus on brevity for reasons of brevity. For the discussion of sampling and resampling operations, we emphasize procedures specifically aimed at increasing resolution (upsampling, superresolution) as already described in the dimensions section.

An extremely interesting issue is the feature extraction processes. The most common approach in processing remotely sensed images is to extract thematic information in the form of maps, possibly recognizing certain types of objects. However, traditional methods cannot directly deliver a solution and a feature extraction step is needed beforehand. However, recent ML-based algorithms, in particular, convolutional neural network (CNN) and deep learning-based deep neural network (DNN) tools, combine the traditional classification with a feature extraction step; feature vectors that are computed and extracted separately are not included in the method, they are only used in its intermediate memory usage without external storage.

Segmentation plays a critical role in interpreting and managing vast amounts of data captured by satellite or aerial sensors. AI-based segmentation in remote sensing data processing uses machine learning and deep learning techniques to automate and improve the segmentation process. These AI methods learn from large datasets to identify patterns and features that may be difficult to detect using manual methods or traditional automated techniques. The best-known and rapidly spreading methodology is semantic segmentation. Semantic segmentation is called "semantic" because it involves understanding and labeling each pixel of an image with meaningful class-specific information, such as distinguishing roads from buildings [Huang et al., 2023; Lv et al., 2023; Yu et al., 2023; Yuan et al., 2021].


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Clustering in image analysis has a long history dating back to the early ages of remote sensing. To set an example ISODATA, k-means are implemented in many tools; including the very old AI-based solutions, like fuzzy k-means [Gustafson and Kessel, 1978].

Nowadays, clustering can be based on various AI-based algorithms like K-Means Clustering, Fuzzy C-Means Clustering, Hierarchical Clustering, Spectral Clustering or Deep Learning-based Clustering (using autoencoders, convolutional neural networks, etc.). Extensive state-of-the-art literature is available on that; just a few articles to illustrate this range are: [Johnson, 1967; Li and Qiu, 2022; Ng et al., 2001; Venkata et al., 2020; Zhao et al., 2022].

Classification of remotely sensed images means the translation of the acquired image/raster/point cloud data into different (thematic) categories. This is certainly the processing with the highest incidence of AI tools developed in RS image data analysis. These include shallow and deep neural networks, convolutional neural networks, recurrent neural networks, graph neural networks, autoencoders, support vector machines, or random forests. [Adegun et al., 2023; Ball et al., 2017; Belgiu and Dragut, 2016; Chen et al., 2024; Hu et al., 2022; Ishikawa et al., 2023; Lyu et al., 2016; Ma et al., 2019; Mountrakis et al., 2011; Phan et al., 2020; Piramanayagam et al., 2016].

## 4. AI can not only be used for good purposes

### 4.1 Fake satellite imagery

Introducing the research work of Yunya Gao, Dirk Tiedea, and Stefan Lang which dug deeply into assessing the quality of images in the era of generative AI, and how can fake images be harmful rather than only beneficial, perhaps can be recapitulated as follows:

- Image-to-image (I2I) translation approaches in deep learning, made it possible to translate satellite imagery directly to map-like images which can save much effort. (Even though these I2I approaches have not been fully applied in reality, they have a high potential for fast urban mapping in the future.

- While fake satellite imagery is not a new problem (Abady et al., 2022), many variants of the segment anything model (SAM), Grounded SAM in particular, make it much easier than before to produce such fake satellite imagery.

- Fake satellite images can pose a threat to the reliability of mapping results generated by I2I approaches. Despite the stunning performance of these artificial intelligence (AI) techniques, we cannot ignore their potential danger of creating fake satellite imagery more easily and thus more fake geo-information for malicious purposes.

- Isola et al., 2017 proposed an I2I translation approach named Pix2Pix GAN (Generative Adversarial Network) that can directly translate satellite imagery into map-like images, which can jump over several steps and save a lot of time for map generation.

- Therefore, the reliability of input satellite imagery can be substantial for crosschecking by humans before publishing the generated maps to the public. Nevertheless, the fast development of variants of SAM, especially Grounded SAM, facilitates the easy production of fabricated satellite imagery, which brings more unreliability to the generated maps.

Over the last few years, deep learning methods enabled the automated processing and analysis of large satellite image datasets. Hundreds of applications and operational solutions validate various benefits of deep learning (DL) methods, particularly for large datasets.

DL has initially been widely associated with convolutional neural networks (CNN). Today, a variety of neural network architectures of DL are widely used in image analysis, including CNN, recurrent neural networks (RNN), long short-term memory, encoder-decoder, and autoencoder models, generative adversarial networks (GAN), vision transformers (ViT), capsule networks, and gated recurrent units.

But as with any technology, misuse or use that harms the public cannot be completely prevented. In particular, Generative Adversarial Networks (GAN) are known for their potential to generate something that does not exist or to alter an image showing a real-world situation. They can therefore be used for the production of fabricated satellite imagery that shows an “alternative reality”. This potential is not necessarily bad. It can be used for scientific simulations, e.g., within the realm of climate change modeling. However, GANs can also be used to create deepfake satellite imagery.

The term deepfake refers to synthetical media (e.g., images, audio, videos) that digitally alter the original content to something else. A well-known example is to manipulate a photo of a person to get the impression of being another person or to manipulate the context and the interpretation of the particular situation. While such techniques can be employed for the better or worse, a severe danger arises if such powerful methods are used for malicious purposes or to disseminate misinformation.

Unlike images of persons, attempts to fake satellite images are so far rare, but there is a need for developing methods to verify or falsify images – a topic that was hardly been thought of some ten years ago.

The few examples that are documented (see e.g., Zhao et al. 2021) mainly use deep learning algorithms, e.g., Cycle-Consistent Adversarial Networks (CycleGAN) that is one of the vibrant of the GAN family. It is documented that these algorithms are capable of replacing objects on the ground with different objects seen from other high-resolution satellite imagery.

This matter has evoked geographers’ concern about the spread of the fabricated satellite imagery, and thus, misleading people in multiple ways by hoaxes (GeographyRealm 2021). Still, as a brief search in Scopus and Google Scholar shows, the topic yields very few hits within the six-digit number of satellite image analysis related literature over the last five years.

Nevertheless, it will be an important research topic over the next upcoming years, also with security and defence angels if political adversaries use fake imagery to fool their enemies with deepfake satellite imagery. The US National Geospatial-Intelligence Agency projected a scenario where military forces who followed

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a wrong route provided by military planning software based on fake imagery are at serious risk (TheVerge.com 2021).

The recent development of the Segment Anything Model (SAM) makes it even easier to create such deepfake satellite imagery. This will likely attract more attention of geoinformation users worldwide. SAM is a powerful AI model designed by Meta AI that can segment any object from images by several clicks. Grounded-SAM combines Grounding DINO and SAM to allow users to detect objects by text inputs as well as replace the target objects with other objects by text inputs.
Algorithms such as CycleGAN can produce deepfake satellite imagery but they still require sufficient deep learning knowledge, adequate computing resources, and longer training time. For Grounded-SAM users, all they need to do is to change prompt text inputs for detecting target objects and replacing them with other objects within minutes.

Within her PhD work, Yunya Gao and her supervisors Prof. Stefan Lang and Prof. Dirk Tiede tested the capability of the current Grounded-SAM demo to produce deepfake satellite imagery with multiple examples from refugee camps through Google Earth software. Refugees belong to a vulnerable group that requires humanitarian aid from organizations such as the United Nations or non-governmental organizations. These organizations rely on satellite imagery to a great extent to design logistics planning due to the difficult access of these areas and lack of on-site information.


Figure 01: Example refugee camp real image

Operationally, we only need to ask the model to detect white, bluish, or greyish rectangles or patches and replace them with barren land or grassland from the background.

The Grounded-SAM can usually generate highly deceivable satellite imagery after several trials, which can be a significant threat to organizations that rely on accurate geoinformation.

We save the real and output fake satellite imagery together with their locations in KMZ format that can be opened by Google Earth software in this Google Drive link.

The locations of selected examples can also be opened through these links directly, example 1 2 3, example 4, example 5, example 6, example 7.

After analyzing these real and fake satellite imagery examples (Fig. 01 and Fig. 02), the team around Yunya Gao considers this fake satellite imagery from Ground-SAM to be potentially harmful such data becomes open-sourced in social media or press.


Figure 02: Example refugee camp faked image

However, from these very short, preliminary observations and tests we can conclude with certainty that these developments create a great need for research into the verification and falsification of satellite images (Abady et al. 2022). Likewise, the scientific community needs to develop ethical regulations for using such powerful SAM models for satellite imagery or developing even more powerful algorithms to identify the nature of open-sourced satellite imagery.

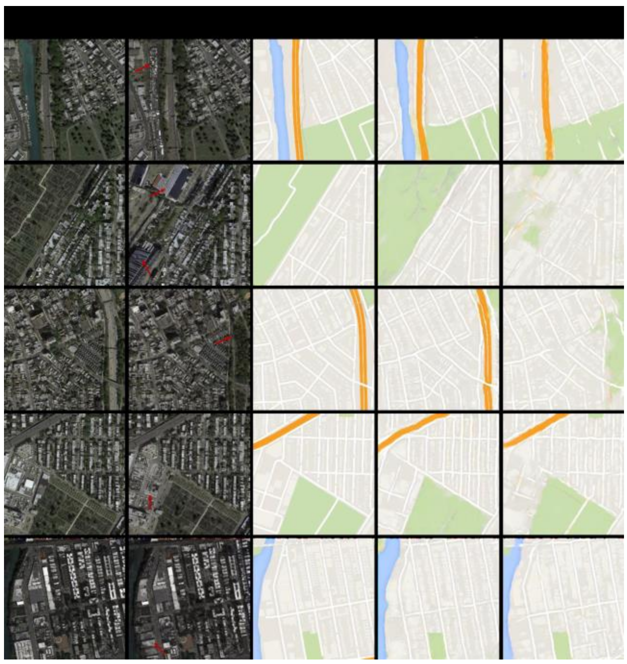
Figure 3. Examples of real satellite images from Google Map satellite imagery, fake satellite images produced by Grounded SAM, real maps from Google Map, generated maps based on real and fake satellite imagery by Pix2Pix GAN.

Red arrows highlighted the main changes in fake satellite imagery compared to real satellite imagery.


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## 5. Quality Aspects Related to Applying AI in Data Acquisition

The automation of data acquisition has been looked into continuously by scientists since the beginning of the era of applying the technology of surveying till date (https://en.wikipedia.org/wiki/Surveying) and is certainly kept further developing to date, aiming to overcome the direct physical interaction with all types of city objects and infrastructure elements. Hence, satellites are also set to orbit the Earth continuously and collect data using a variety of sensors that serve a certain range of acquisition demands (Danielle et al, 2018).

However, satellite-based data collection alone isn't enough to satisfy all scales and details, so other means of automated data collection also exist and are continuously being developed. Examples of that are field surveying, different types of mobile laser scanners, transactional updates, indoor mapping, drone photography, aerial photography, public or crowed source data acquisition, and finally IoT Internet of Things via sensors and Big Data.

AI and its sub-applications machine and deep learning also occupied its place on the deck of development, and it's becoming the most significant method of development and innovation in the field of geospatial science and technology likewise in other disciplines.

Among the significant areas of applications perhaps remote sensing got the largest slice, as AI got implemented in image interpretation and classification, image enhancement including image generation, also in interpreting and automating data collections from lidar point clouds, and many more (Bhargavi et al., 2023).

The quality of interpretation and classification workflow is subject to the elements discussed in Table- 1.

Those elements and more affect the quality of the image interpretation and classification process. Some of these elements are highlighted here to lift the curtain on a play that the geospatial community is expected to investigate further.

The procedure of implementing AI for classification in many practical cases starts with selecting the method/methods and systems, this can be either an open method or an open method that is embedded into a system or commercial software.

The quality of the results thus, at first is subject to the AI deep learning method used or embedded within a system, a comprehensive explanation including using Deep Learning for image interpretation and classification was provided by (Gui et al, 2024). The method used for reliability is certainly evaluated through the level of conformity of its produced results with reality or the truth.

For example, U-Net and other sister methods are special types of Convolutional Neural Networks (CNN) that have proven advancement in the semantic classification of pixels. The methods proved reliable in classifying certain thematic infrastructure layers, which was also proved when tested in combination with other methods within a short study to assess the results of a thematic mapping project conducted by the AI team of GISCD in Dubai. (The methods and corresponding layers are illustrated in Table_2.

| Topic | Note |
|---|---|
| Image Characteristics | Effects of geometric and radiometric parameters |
| Data classes | Defining classes that make sense |
| Data quality aspects | Can the produced results be reliable for usage and to what limits? |
| Purpose of usage | Targets defined paths |
| Change Detection | Decide when and where a change matters |
| Conventional classification methods | What's new with AI versus conventional |
| Labeling and manual work | Why AI if we are labeling everything, what are the elements of a good labeling practice |
| AI and models | Modelling aspects |
| Model limitations | How and who decides that |
| Model transferability | Good models can be reused |
| Model reliability | The environment matters |
| Quality Assurance | Workflow based |
| Quality control | Before usage and aft |
| Quality of produced data | Affects decision making |
| Resource and Time quality aspects | Who, how many, how long |
| Open source Imagery | Is it enough? |
| High-resolution imagery and applications | Needed for some applications |
| Produced Vectors | Cartography and enhancements |
| Bands | Is RGB enough for AI |
| Attributes | Can I automate that? |

Table- 1 ( Brainstorming quality aspects for Interpretation)

| Type | Characteristics | Geo-classes |
|---|---|---|
| Model 1 - UNET | Multi Class | Car Parks<br>Buildings<br>Road Network<br>Vegetation Land<br>Trees<br>Grassland |
| Model 2 - BarchNorm UNET | Multi Class | Water Body Layers<br>Open areas<br>Bare earth<br>Vegetations |
| Model 3 - Mask RCNN | Binary & potentially Multi Class | Buildings<br>Potentially also:<br>Water bodies Layers<br>Open areas<br>Bare earth<br>Vegetations |
| Model 4 – SpaceNet | Binary | Roads |

Table 2: Models compared for reliability in interpretation

As shown above, the study yielded that different methods are more reliable in specific types of classes, but this is just an example and yet needs more testing to prove the level of effectiveness as many other factors play roles in changing the game of reliability. Factors such as the type of image and the characteristics of the area are among many factors that can increase or decrease the values measured via the confusion matrix like accuracy, precision, recall, or another evaluation method.

The purpose of mapping define many facts like what type of image is to be classified. The spectral resolution plays a big role in this manner as AI can only produce what can be seen or observed. But in many cases, budgets and image availability can cause selecting a different path. What you can teach the machine is what can be labeled, and only observed objects on an image can be labeled, but the number and type of bands can play a hidden role in the learning process.

Further, how much percentage of the image should be labeled and how well should it cover the different variety of objects will also affect the reliability of the final model. Then a certain area of the image is to be left unlabeled so that it can later be used to assess the results of interpretation and classification (Nuaimi et al, 2024).

## 6. Discussion & Conclusion

Remote Sensing Data quality is certainly largely affected by the thriving AI and the Deep learning era. Many aspects and considerations are open to scientific research and testing including the effects of Generative AI, the effectiveness of using the models for mapping, vector data production, change detection, the evaluation of the so-called super-resolution and enhanced images, and how it adds to the ability of interpretation and classification. The ability to judge produced images and produced data, and subsequences to decision-making is also hectic to smart city management.

Moreover, it is clear that further consideration should be given to analyzing data quality in the remote sensing lifecycle and how the different quality measures are correlated with the advent of AI and implementations.

The following points are open for further discussion;

**Generative AI for Data Augmentation:** Can Generative Adversarial Networks (GANs) be effectively leveraged to create synthetic satellite imagery that supplements real-world data? How can this synthetic data be used to improve the training and performance of feature extraction models?

**AI-powered Mapping and Vector Data Production:** How can AI models be optimized to produce high-quality, accurate maps and vector data from remote sensing imagery? What are the limitations and potential biases to consider?

**Change Detection with Enhanced Efficiency:** Can AI models be used to streamline and improve change detection processes, allowing for more timely and accurate monitoring of Earth's dynamic landscapes?

**Super-Resolution and Enhanced Imagery: A Double-Edged Sword:** While super-resolution techniques can increase image detail, how can we ensure these enhancements don't introduce artifacts or mislead interpretations? How can we effectively judge the quality and reliability of such enhanced data?

**AI-Driven Decision Making: The Need for Critical Evaluation:** As AI plays a growing role in interpreting and classifying remote sensing data, developing robust methods to assess the quality and trustworthiness of AI outputs becomes crucial. This ensures that downstream decision-making processes rely on reliable information.

Beyond these specific areas, the paper emphasizes the need for a broader look at data quality throughout the entire remote sensing lifecycle. How do established quality metrics need to be re-evaluated and potentially redefined in the context of AI-driven data processing and analysis? How can we ensure that AI itself doesn't inadvertently introduce new quality concerns?

In conclusion, the relationship between AI and remote sensing data quality is symbiotic. AI offers powerful tools to enhance data quality, but it also necessitates reevaluating traditional quality assessment methods. By fostering ongoing research and collaboration between AI experts and remote sensing specialists, we can unlock the full potential of this transformative era in Earth observation.

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